EEG Classification Using Different Feature Extraction Techniques for Emotion Recognition

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Abstract

Brain Computer Interface (BCI) is becoming increasingly popular. Our paper focused on an applied of it that is called recognizing emotion from human brain activity, measured by EEG signals. EEG signals were analyzed and classified into three emotions—happiness, sadness and normal. For emotion recognition, Radial Based Function (RBF) is applied to classify the emotional signals and feature extraction techniques are investigated. Using gathered data under EEG signals emotion stimulation experiments, the classifier is trained and tested. After applying classification and different feature extraction methods to 300 EEG time series, we concluded that frequency-band energy features outperformed other methods in the emotion assessment.

Keyword: Classification, Feature Extraction, BCI, EEG, Emotion, RBF

I. Introduction

In recent years, BCI and feature extraction have attracted a great interest ranging from medicine to military objectives. To facilitate BCI assembly, a useful method of feature extraction from EEG signal is needed (Mayaud et al, 2003). The brain is a complex network of interconnected neurons. The connection between neurons is done via the exchange of electrical activity. These activities can be used to detect and interpret of individual intention and mental state. Since emotions play an important role in our mental life and many problems in human psychology and society are caused by emotions so we decide to research in this field. One of the important emotion theories is the cognitive theory in which the brain is the onset and center of emotional activity. The electroencephalography (EEG) is the most common method in order to record these brain activities. The recording of the EEG signals is performed by fixing an electrode on the subject scalp using the standardized electrode placement scheme (Figure 1). However, there are many sources of artifacts. The signal noise which can set in when signal is being captured will adversely affect the useful feature in the original signal. The major sources of the artifact are muscular activities, blinking of eyes during signal acquisition procedure, and power line electrical noise. Many methods have been introduced to eliminate these unwanted signals. Each of them has its advantages and disadvantages. Nevertheless, there is a common path for EEG signal processing (Figure 2)(Kousarrizi et al, 2009). The first part after acquisition of signal is removal of artifacts. The third step in the operation is the feature extraction scheme which is meant to determine a feature vector from a regular vector. Extracting informative and discriminative features from EEG signals is often of crucial importance for representing and classifying patterns of brain activations. A feature is a distinctive or characteristic measurement,
transform, structural component extracted from a segment of a pattern. Statistical characteristics and syntactic descriptions are the two major subdivisions of the conventional feature extraction modalities. Feature extraction scheme is meant to choose the features or information which is the most important for classification exercise (Chanel et al, 2006). The final stage is signal classification which can be solved by linear analysis, nonlinear analysis, support vector machine, adaptive algorithms, clustering and fuzzy techniques, and neural networks.

II. Acquisition protocol

Data was acquired from 10 participants, 6 males, 4 female. For EEG's we used a Biosemi Active Two device with 64 electrodes (plus 2 for reference). We sampled signals at a 1024 Hz rate. For each recording, the participant equipped with the above sensors was sitting in front of a Laptop computer screen at first screen was dark. A white cross was then drawn on the screen center for a random period of 2 to 4 seconds, to attract user's attention and avoid accustoming. An IAPS image was subsequently displayed for 8 seconds. Finally, we asked the participant to self-assess their emotion. After recording EEG signals, signals were preprocessed by a band-pass filtering to keep frequencies in the 4-45Hz range. This allowed us to remove unwanted effects like power line noise. Also we identified Eye blinks as high-variance parts and removed by subtraction from the signals.

III. Feature Extraction:

With the advent of electroencephalography, the study of EEG has been started and now there is vast variety of methods to the extraction of quantitative features from an EEG signal. Non-linear dynamics methods to the problem of the description of an EEG were relatively successful. Another one is statistical approaches which seem to be the most feasible and theoretically satisfactory methodology for the quantitative analysis of the EEG signal up to now.
Mathematical methods are for extracting features from EEG signals. For EEG classification there are various features such as wavelet coefficients, autoregressive model parameters, and signal energy in different frequency bands which have been used. An important problem with EEG classification is the huge number of features which, it comes from the fact that EEG signals are no stationary, thus features must be computed in a time-varying manner and the number of EEG channels is large. In this paper we applied the autoregressive (AR) model coefficients, band power and standard, because they investigate the EEG signal in different aspects. They are related to power spectrum, frequency domain and average of the EEG signals, respectively. In following a short review of feature extraction methods for extracting from EEG signals are investigated:

A. Standard features

The physiological features can be considered as standard because of their frequent use for emotion assessment. Only the features that were used in this study are described. By assuming that each measured signal is generated by a Gaussian process with independent and identically distributed samples, the two physiological features that can be used to characterize a physiological signal are its mean and its standard deviation:

\[ \mu_x = \frac{1}{N_s} \sum_{n=1}^{N_s} x(n) \]
\[ \sigma_x = \sqrt{\frac{1}{N_s} \sum_{n=1}^{N_s} (x(n) - \mu_x)^2} \]

Where \( (n) \) is the value of the signal \( x \) (an EEG electrode signal, GSR signal, etc.) at sample \( n \) and \( N_s \) is the number of samples in a trial.

In order to evaluate the trend of a signal \( x \) over a trial, the average of the signal derivative can be computed as:

\[ \delta_x = \frac{1}{N - 1} \sum_{n=1}^{N-1} (x(n + 1) - x(n)) = \frac{x(N_s) - x(1)}{N_s - 1} \]

Finally the maximum and minimum of a signal can also provide information concerning the range of the signal amplitude:

\[ \text{Min}_x = \min x(n), \quad \text{Max}_x = \max x(n) \]

Those features are quite general and can be applied to a wide range of physiological signals (Chanel, 2009).

B. Autoregressive Method

Autoregressive (AR) parameters have been used successfully in EEG analysis and the AR model can well describe the stochastic nature of EEG. However, the model parameters of AR are
assumed to be unchanged over time. AR methods estimate the power spectrum density (PSD) of the EEG using a parametric approach. Therefore, AR methods do not have problem of spectral leakage and thus yield better frequency resolution unlike nonparametric approach. Estimation of PSD is achieved by calculating the coefficients, that is, the parameters of the linear system under consideration. Two methods used to estimate AR models are briefly described below. (Subasi et al, 2005)(Faust et al, 2008)

C. Energy bound

It is shown that the EEG contains different frequency components, which can show different brain states and contain the discriminative information. Normally, EEG is classified as delta=[less than 4 Hz], theta=[4-8 Hz], alpha=[8-13 Hz], beta=[13-30 Hz] and gamma=[more than 30 Hz]. Band power feature reflects the power in these five bands at each electrode position. First, the signal is filtered in determined frequency ranges using band-pass filter (Butterworth filter of order five). Second, each sample is squared and is averaged over a one-second interval (Parvinnia et al, 2014).

IV. Radial Basis Function Networks classification

The radial basis function (RBF) network comprises one of the most used network models, which address the problem of curve-fitting and approximate in high-dimensional spaces. Learning in this case is equivalent to finding an interpolating surface in the multidimensional space that provides a best fit to the training data, measured by preselected statistical criteria. The RBF network consists of one hidden layer of basis functions, or neurons. At the input of each neuron, the distance between the neuron center and the input vector is calculated. The output of the neuron is then formed by applying the basis function to this distance. The RBF network output is formed by a weighted sum of the neuron outputs and the unity bias shown.

Figure 3. Radial Basis function network

Figure 3 illustrates an RBF network with inputs $p_1, ..., p_n$ and output $y$. The arrows in the figure symbolize parameters in the network. The RBF network consists of one hidden layer of basic functions, or neurons. At the input of each neuron, the distance between the neuron center and the input vector is calculated. The output of the neuron is then formed by applying the basis function to this distance. The RBF network output is formed by a weighted sum of the neuron outputs and the unity bias shown. In this study the data were divided into 20 categories, training and testing. We devote 80% of all data for training and 20% for test (figure 4).
TABLE I
COMPARISON OF DIFFERENT FEATURE FOR EEG

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Standard mean</th>
<th>Standard deviation</th>
<th>Energy bound</th>
<th>AR</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBF(0.1)</td>
<td>58%</td>
<td>63%</td>
<td>80%</td>
<td>75%</td>
</tr>
</tbody>
</table>

V. Conclusion

Three of the well-known methods for power spectrum, frequency domain and average of the EEG signals were investigated. The main problem in the classification of EEG signals is the quality of the recorded signal, which can be different during the experiment. After applying classification and different feature extraction methods to 300 EEG time series, we concluded that frequency-band energy features outperformed other methods in the emotion assessment. For future works it suggests, that other classifiers and other type of EEG signals can be used.

6- References:


